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Peer And Neighborhood Influences On Substance Use Among Emerging Adult Males: An Activity Spaces Approach

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INTRODUCTION

Alcohol and substance use are common among emerging adults, with estimates in the US near 70% for past year alcohol use and 43% for illicit drug use.[1] Use of these substances may result in various adverse outcomes, including mortality, unsafe sex, poor mental health, and crime.[2-6] In addition, heavy use early in life may lead to subsequent substance abuse or dependence.[2,7] Males are particularly susceptible to problems with alcohol and substances and are at greater risk of becoming regular alcohol and illicit drug users and develop substance abuse and dependence.[1,6] These problems are particularly striking for minority men. Although minority men are less likely to use substances when compared to whites, they are more likely to develop substance abuse, dependence, and problems from substance use.[1] These studies stress the importance of looking at substance use among emerging adult minority men.

One potential factor for alcohol and marijuana use during emerging adulthood is peer influence. Peer influence has emerged as a significant predictor of substance use such that affiliation with substance using peers promotes an individuals' use of illicit drugs or alcohol.[5-8] Young adults who interact within social networks with higher concentrations of alcohol and drug users are more likely to use alcohol and drugs themselves.[9,10] For example, one study found that individuals are 50% more likely to drink alcohol if one of their social network members drink[11] There is limited literature elucidating how these networks interact with other aspects of person's social context. One potential aspect of social context that might influence how social networks influence behavior is the environmental influence of the geographical space where networks congregate.[12]

Socioeconomic neighborhood characteristics, including low income and area deprivation indicators, have been linked to greater alcohol and illicit drug use,[13,14] though evidence is mixed.[15] Neighborhoods with social disorganization, poverty, and crime have been linked to increased risk for HIV and substance use.[7] Further, greater access to substances may facilitate substance use. A recent systematic review found a modest association between alcohol outlet density and higher odds of heavy alcohol consumption, though findings were mixed across studies.[16] As drug and alcohol use often co-occur,[17] access to alcohol may also be related to drug use patterns among young adults. In contrast, access to places for recreational purposes or churches may be protective against substance abuse.[12] These findings suggest that the geographic context may influence risk behavior such as substance use.

Despite substantial literature examining various contextual influences on substance use, this area of study is limited in several ways. First, many studies utilize a single location, often individuals' place of residence, to examine neighborhood influences on alcohol or illicit drug use. This method fails to capture mobility of individuals, which may be particularly relevant for emerging adults who may spend less time at home and more time in peer contexts during this period.[18] Research has shown that neighborhood characteristics of places where individuals regularly spend time have more of an influence on risk behavior than neighborhood characteristics of home residence, demonstrating our need to expand the notion of how geographical context may influence health. Second, much of the social network literature examines social networks as static entities rather than fluid depending on location and context. Recently it has been suggested that we need to better understand how different social and geographical contexts contribute to unique risks at different activity spaces.[7,12,19]

Research utilizing event-based approaches to understand substance use behavior addresses some of these gaps. This approach accounts for fluid compositions of individuals and characteristics that may vary according to places individuals travel to routinely (known as activity spaces).[7,19,20] However, even within this area few studies utilize comprehensive data from all activity spaces identified by individuals. Examining peer and neighborhood influences at each activity space may better elucidate the complex relationships between social networks, geographical context, and substance use. The present study aims to utilize an event-based, activity spaces approach to examine alcohol and drug use among emerging adult men. Specifically, we aim to 1) assess the influence of peer networks and neighborhood-level characteristics (socioeconomic and built environment characteristics) as independent predictors of substance use, 2) examine whether activity spaces characterized as risky or non-risky differ by peer network influence and neighborhood-level characteristics, and 3) assess whether the associations of peer and neighborhood-level characteristics and substance use differ for risky and non-risky locations (e.g., whether risk of location moderates peer and neighborhood factors).

METHOD

Procedures

The study included young men participating in a longitudinal study of social networks, health behavior and health outcomes among emerging males. The recruitment process began with identification of emerging adult men who were recruited from areas and organizations that we previously identified as having high frequencies of young men. Snowball sampling was used to recruit friends of participants. Inclusion criteria for all participants included: (a) male gender; (b) age 18-25; (c) English-speaking; (d) heterosexual; (d) in possession of a cell phone with texting capabilities, and ability to maintain cell phone service.

Data were collected at 3 time points: baseline (Time 1), 3 months after baseline (Time 2), and 6 months after baseline (Time 3). During the baseline appointment, research staff obtained written informed consent. Participants completed structured interviews via audio computer-assisted self-interviews (ACASI) as well as audio-recorded face-to-face interviews with trained research staff. Participation was voluntary and confidential, and all procedures were approved by the Yale University Human Investigation Committee. Participants were remunerated a minimum of $150 and a maximum of $300 for time and effort.

Demographic variables were collected at the baseline visit (Time 1). Activity space information was assessed either 3 months (Time 2) or 6 months (Time 3) following the baseline visit. Predictors and outcomes were assessed at the same time point the activity space exercise was completed.

Measures

Activity spaces and mapping information was assessed using techniques adapted from Mason and colleagues.[19] Participants were instructed to list all locations visited in a typical week. After obtaining a complete list of locations, participants were asked the following about each place: days per week visited, whether visited during the week or weekend, time of day visited (e.g., day or night), and members of their social network who also spend time at the location. In addition, participants were asked if they use alcohol or drugs at each location. Further questions were asked regarding frequency of use, alcohol and drug use by friends, and features of each location that facilitates each behavior. No participant endorsed hard drug use (e.g., heroin, cocaine) during the activity spaces exercise; therefore we focused our drug use variables on the use of marijuana. Activity spaces were classified as risky if marijuana was used by the participant at that location or if the participant endorsed alcohol use at that location and reported drinking more than 5 alcohol drinks when drinking at that location, which is consistent with the definition of binge drinking.[5,21] All other locations were classified as non-risky. Risky spaces were further dichotomized into risky alcohol spaces and risky marijuana spaces.

Once information was obtained about participants' activity spaces, the website MapFab was used to drop a place marker for each location on a map. Participants were instructed to provide addresses when possible, or, in the absence of addresses, identify cross streets or landmarks to pinpoint the location of each activity space. Individual maps were exported to Google Earth, which was used to extract geographic coordinates for each activity space.

Predictors

Network quality was based on a measure of negative-positive network influence adapted from Mason and colleagues.[12,19] Network quality was assessed separately for each activity space for all participants and incorporated peer participation in alcohol or marijuana use and peer influence. Participants indicated which peers that spend time with the index at each location participated in alcohol or marijuana use at each location. Peers received a score of either -4 (substance user) or +4 (substance non-user). To assess positive influence, participants were asked whether each “peer tries to get me to do the right thing” (range 0 to 4, with 0 indicating no attempt to influence and higher numbers indicating more positive influence). To assess negative influence, participants were asked whether each “peer tries to get me to do what feels good even if there may be consequences” (range 0 to -4, with 0 indicating no attempt to influence lower numbers indicating more negative influence). Scores were summed for each network member such that each network member score ranged from -8 to +8. A total score for each location was calculated by summing the scores for all network members listed at that location weighted by the perceived closeness of the participant with the network member (e.g. How close are you with peer?). Perceived closeness ranged from 1 to 7 with a score of 7 indicating more perceived closeness. Locations with no peers present received a zero, indicating a neutral network quality. Higher network quality scores indicated a more positive network quality, whereas lower network quality scores indicated more negative network quality.

Neighborhood level characteristics included both physical built environment and socioeconomic characteristics. Physical built environment characteristics included off-premise alcohol outlets, police stations, churches, libraries and parks. These characteristics were chosen to reflect empirical evidence for an association of place with outcomes (e.g., alcohol outlets, churches),[12,22] conceptual links between the place and outcomes (e.g., police stations, parks),[23,24] or common recreational places that emerged from the activity spaces exercise (e.g., libraries). Google Earth was used to search for each category of physical built environment features and obtain geographic coordinates for each location. This is an attractive method, as it is not resource-intensive and has been shown to be reliable for street level characteristics implicated in health outcomes such as food outlets and liquor stores.[25] Half a mile buffers were computed around each activity space, and a count of all physical built environment characteristics by category was obtained. Socioeconomic characteristics included median household income, percent unemployment, percent owner-occupied housing, and the EASI Total Crime Index. The EASI Total Crime Index is a composite crime variable that includes murder, forcible rape, robbery, aggravated assault, burglary, larceny and motor vehicle theft.[26] Violent crimes are given greater weights in the computed variable, and higher values indicate greater crime.[26] The national average for the EASI Total Crime Index is 100. Simply Map was used to obtain data for median household income and crime at the census-tract level.

Outcomes

Problem alcohol use was assessed with the 3-item version of the Alcohol Use Disorders Identification Test (AUDIT). Previous studies have indicated that the 3-item AUDIT is comparable to the longer 10-item AUDIT in detecting problematic alcohol use behavior.[27] Participants were asked questions regarding frequency of alcohol consumption, amount of alcohol consumption on a typical day of drinking, and how often six or more alcoholic beverages are consumed in one sitting. Response choices for each item ranged from 0 to 4. A total problem alcohol use score was computed by summing the responses for the three items, and ranged from 0 to 12 with higher scores indicating more problematic alcohol consumption.

Days of marijuana use was included as a continuous variable indicating the number of days the participant used marijuana within the last month.

Multiple daily use of marijuana was included as a dichotomous variable indicating whether or not the participant endorsed typically using marijuana 2 or more times per day.

Data Analysis

Descriptive statistics were generated for demographic, activity space, and outcome variables. Next, continuous predictors and outcomes were standardized and separate multivariable models were generated for alcohol and marijuana use and risky space indicators using Generalized Estimating Equations (GEE) with locations nested within individuals. GEE is a method similar to multi-level modeling in that it corrects for clustered and correlated data.[28,29] The models controlled for number of peers present at each activity space and individual sociodemographic factors (age, income, education, race/ethnicity) that were significant ($p<0.05$). To determine whether risky activity spaces moderated the effect of the predictors on alcohol and marijuana outcomes, a risky space by predictor term was added to the models one at a time. To interpret the nature of any interactions simple effects were conducted. Clusters of high and low risky spaces were examined using the Getis-Ord Gi statistic.[30] This statistic identifies clusters of points with values higher in magnitude than you might expect to find by random chance.[30] The Gi statistic is based a Z score which represents the statistical significance of clustering. We identified a statistically significant spatial clusters of high values (hot spots) using this metric and visually identified areas of uniform *p* values. All statistical analyses were performed using SAS 9.3 while spatial computations and visualizations were performed using ArcGIS 10.2.

RESULTS

The sample consisted of 70 emerging adult males (Table 1). Participants were predominantly African American (77%) or Hispanic (20%), while the remaining participants were White (3%). The mean age was 20.61 (SD=2.09) while the mean education was 13.03 years (SD=2.1). Past year alcohol use was endorsed by 79% of the participants and among all participants the mean problem alcohol score was 3.38 (SD=2.98). Lifetime marijuana use was endorsed by 77% of the participants, and among all participants the mean days smoked in the last month was 12.17 (SD=12.35). Thirty percent of participants reported using marijuana more than one time per day.

Participants identified 397 activity spaces with a mean of 5.88 spaces (SD=2.09) per participant of which 1.19 (SD=1.53) were risky and 4.70 (SD=2.49) of which were non-risky. Figures 1 shows the identified activity spaces and risky and non-risky activity spaces, while characteristics of the activity spaces are shown in Table 2. The mean number of peers present at each space was 1.94 (SD=2.03) and the mean network quality score was 46.75 (SD=91.05). Number of physical built environment features within 0.5 miles of each activity space ranged from a mean of 0.51 features (libraries, SD=0.74) to 10.06 (churches, SD=8.46). The mean crime index for the activity spaces was 67.20 (SD=56.10) and the median household income was $47,251.79 (SD=$19,658.25).

Cluster analysis using the Gi statistic revealed statistically significant clustering of risky spaces (2). Visual analysis revealed one area of clustered high risk spaces with uniform *p* values in the southeastern portion of downtown New Haven.

Table 3 shows the results of models examining alcohol and marijuana use as outcomes using GEE. Lower network quality at the activity spaces was significantly associated with a higher number of days of marijuana use (B=-0.0033, 95%CI=-0.0052, -0.0015, $p<0.005$), use of marijuana more than one time per day (B=-0.0183, 95%CI=-0.0292, -0.0074, $p=0.001$), and higher scores for problem alcohol use (B=-0.0132, 95%CI=-0.0223, -0.0040, $p<0.005$). No other predictors were significantly associated with marijuana or alcohol use.

Table 4 shows the results of models examining risky spaces (total), risky alcohol spaces and risky marijuana spaces as outcomes using GEE. Lower network quality was associated with risky spaces (defined as risky alcohol or marijuana use; B=-1.1666, 95%CI=-1.5478, -0.7471, p<0.001). A lower count of libraries within a 0.5 mile radius of activity spaces was marginally associated with risky spaces, though this finding did not reach statistical significance (B=-0.3509, 95%CI=-0.7227, 0.0209, p=0.06). When examining risky marijuana spaces separately, lower network quality (B=-1.1153, 95%CI=-1.4836, -0.7471, p<0.001) and lower median household income at the census tract level were associated with risky marijuana spaces (B=-0.5692, 95%CI=-1.106, -0.0324, p=0.04). When examining risky alcohol spaces, lower network quality (B=-0.7257, 95%CI=-1.2015, -0.2499, p=0.003), a higher count of off-premise alcohol outlets (B=0.6701, 95%CI=-0.1275, 1.4678, p=0.10) and a lower count of libraries were associated with risky activity spaces (B=-0.4316, 95%CI=-0.9270, 0.0639, p=0.09). However, both count of alcohol outlets and libraries were only marginally significant.

Next, we examined risky space and predictor interactions for alcohol and marijuana outcomes. No significant interactions for risky space by marijuana use more than one time per day were found. There was a marginally significant interaction between risky space and percent unemployment for number of days of marijuana use (B=0.0025, 95%CI=-0.0002, 0.0052, p=0.07). Simple effects showed that more unemployment in risky space areas was marginally related to greater number of days used marijuana (B=0.0025, 95%CI=-0.0000, 0.0051, p=0.05) whereas there was no relationship between unemployment and non-risky spaces (B=-0.0004, 95%CI=-0.0015, 0.0015, p=0.56). There was a significant interaction between risky space and number of police stations for number of days of marijuana use (B=0.0060, 95%CI=0.0015, 0.0105, p=0.01). Simple effects showed that a higher number of days used marijuana was related to a higher number of police stations in risky space areas (B=0.0525, 95%CI=0.0121, 0.0928, p=0.01) whereas there was no relationship between number of police stations and marijuana use in non-risky spaces (B=-0.0093, 95%CI=-0.0257, 0.0071, p=0.26). There was a significant interaction between risky space and number of churches for number of days of marijuana use (B=0.0050, 95%CI=0.0015, 0.0086, p=0.01). Simple effects showed that a higher number of days used marijuana was related to a higher number of churches in risky spaces (B=0.0043, 95%CI=0.0007, 0.0080) whereas there was no relationship between number of churches and marijuana use in non-risky spaces (B=-0.0009, 95%CI=-0.0026, 0.0008, p=0.32). There was a significant interaction between risky space and the count of off-premise alcohol outlets and number of days of marijuana use (B=0.0037, 95%CI=0.0007, 0.0068, p=0.02). Simple effects showed that a higher number of alcohol outlets in risky spaces was marginally related to higher number of days smoked marijuana (B=0.0098, 95%CI=-0.0003, 0.0199, p=0.06) whereas there was no relationship between the number of alcohol outlets and marijuana use in non-risky spaces (B=-0.0029, 95%CI=-0.0069, 0.0012, p=0.16). Finally, there was a significant interaction between crime and problem alcohol use (B=0.0133, 95%CI=0.0003, 0.0264, p=0.04). Simple effects showed that more crime around risky spaces was related to more problem alcohol use (B=0.0007, 95%CI=0.0001, 0.0013) whereas there was no relationship between crime and problem alcohol use in non-risky areas (B=0.0000, 95%CI=-0.0003, 0.0004, p=0.81).

DISCUSSION

Our study provides evidence that peer and geographical influences are important in alcohol and marijuana use among emerging adult men. Consistent with previous findings, the quality of social networks at activity spaces was an important predictor in substance use.[7,19] Our results extend the work of Mason and colleagues by exploring these associations at each activity space identified by individual participants rather than restricting analyses to a single location identified by participants as risky or safe. Our results suggest that individuals have multiple locations that they regularly frequent, and the risk behaviors of those locations in conjunction with who they hang out with at those locations may influence their risk behaviors.

We examined features of the social and area-level environment that may be important in promoting or protecting against substance use among emerging adult men. Though previous work indicates a higher proportion of young men may use illicit drugs compared to alcohol,[1] prevalence of alcohol and marijuana use in our sample was similar. One possible explanation is social desirability bias, as the activity spaces exercise was conducted via face-to-face in an audio-recorded environment, which may have influenced participants' comfort in endorsing less desirable behavior to study staff.[31]

When examining simple effects of neighborhood level characteristics and peer influences relating to substance use, we found evidence for a relationship between peer influences and substance outcomes but not neighborhood level indicators. However, our results suggest that neighborhood level influences on substance use may be more important for risky spaces than for non-risky spaces. Higher crime in risky activity spaces was related to greater problem alcohol use, which supports prior work suggesting that alcohol use and availability is related to crime perpetration and victimization.[32,33] Greater unemployment in risky activity spaces was related to marijuana use which is consistent with evidence for an association between low socioeconomic characteristics of neighborhoods and illicit drug use.[13,14] In addition, higher numbers of police stations, off-premise alcohol outlets, and churches in risky activity spaces were related to marijuana use. If substance use is more common in high crime or more socioeconomically deprived neighborhoods, we might expect more police stations to be in these areas either as a deterrent or to facilitate more timely police responses to situations.[23] Further, as marijuana and alcohol use co-occur,[17] a high concentration of alcohol outlets may be expected. This may explain the lack of association between alcohol outlets and alcohol use. The association of number of churches in risky spaces and marijuana use was surprising. Previous work has shown religiosity to be protective against substance use among youth[34,35] and we anticipated fewer churches to be related to substance use. However, the presence of churches or other places of worship may not be related to attendance or religious behavior in our sample. These results highlight the complexity of geographical influence on behavior, and the need to extend the notion of space beyond a single location.

Spatial analysis of risky activity spaces revealed that risky spaces clustered in an urban area. This finding is important as frequent travel to activity spaces within these areas of geographic risk may further increase the risk of substance use in urban youth.[1,7] Identification of risky space clusters may assist in targeted interventions to reduce risk for poor outcomes related to substance use.

When examining predictors of risky activity spaces, lower network quality was associated with risky spaces, suggesting that combinations of substance-using alters who are perceived to have a negative influence on the individual may promote substance use. This finding was true regardless of whether the risky space was a risky alcohol space or a risky marijuana space. In addition, fewer libraries were associated with risky spaces and risky alcohol spaces. Many study participants included libraries as part of their activity spaces, suggesting that libraries may be a type of recreational location that may protect against substance use. Risky marijuana spaces were associated with lower median household income at the neighborhood level, further supporting work mentioned previously related to area-level deprivation and illicit substance use.[32,33]

While our study has many strengths, some limitations should be noted. First, our data were cross-sectional, which limits inferences about causality between our predictors and substance use. In addition, our sample size was small, leading to a relatively small number of risky alcohol and marijuana spaces which may have limited our ability to detect statistically significant associations with predictors and outcomes. Further, our analyses were limited to close peers that spend time together in their activity spaces. Consequently, we have no information about other individuals who may also be present at various activity spaces and influence substance abuse behavior. The specific demographic qualities of mostly minority emerging adult men limits our generalizability.

Despite these limitations, our study had numerous strengths including exploring the unique interaction of peer and neighborhood influences on a high risk sample, and expanding the notion of neighborhood influences by including all routine activity spaces used by emerging adult males. Understanding how social networks and neighborhood-level influences confer risks is important in elucidating relationships between these factors and substance use in young people. Event-based approaches provide another layer of context that may aid in understanding how risk changes with different combinations of these factors. Future work would benefit in integrating perceptions of neighborhood level indicators, such as perceived safety, accessibility to alcohol, and neighborhood deprivation as individual-level experiences and beliefs about their environments may be important in understanding patterns of substance use.

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TABLES AND FIGURES

Table 1. Participant demographics and characteristics

Table 1. Participant Characteristics

	Mean	SD	N (%)
Demographics			
Age	20.61	2.09	
Race			
White			2 (3)
African American			54 (77)
Hispanic			14 (20)
Education (yrs)	13.03	2.1	
Income[a]	$18,898	$23,129	
Outcomes			
Alcohol use[b]			55 (79)
Problem alcohol score	3.38	2.98	
Marijuana use			54 (77)
Days marijuana use	12.17	12.35	
Multiple daily marijuana use			21 (30)

$*p < 0.05$

[a]Missing for n=11

Table 2. Activity spaces characteristics

	Mean	S.D.	N (%)
Activity Spaces (N=397)			
Number of activity spaces	5.88	2.09	
Number of alters present	1.94	2.03	
Network quality score	46.75	91.05	
Risky activity spaces			83 (21)
Risky alcohol spaces			24 (6)
Risky marijuana spaces			71 (18)
Census level data			
Median household income	$47,251.79	$19,658.25	
Owner occupied housing (percent)	30.99	23.35	
Unemployed (percent)	14.99	7.65	
Crime Index	67.20	56.10	
Count of places within 0.5 miles of activity spaces			
Police	0.79	0.82	
Parks	0.84	0.95	
Churches	10.06	8.46	
Libraries	0.51	0.74	
Off-premise alcohol outlets	3.06	2.37	

Figure 1. Location of risky and non-risky activity spaces

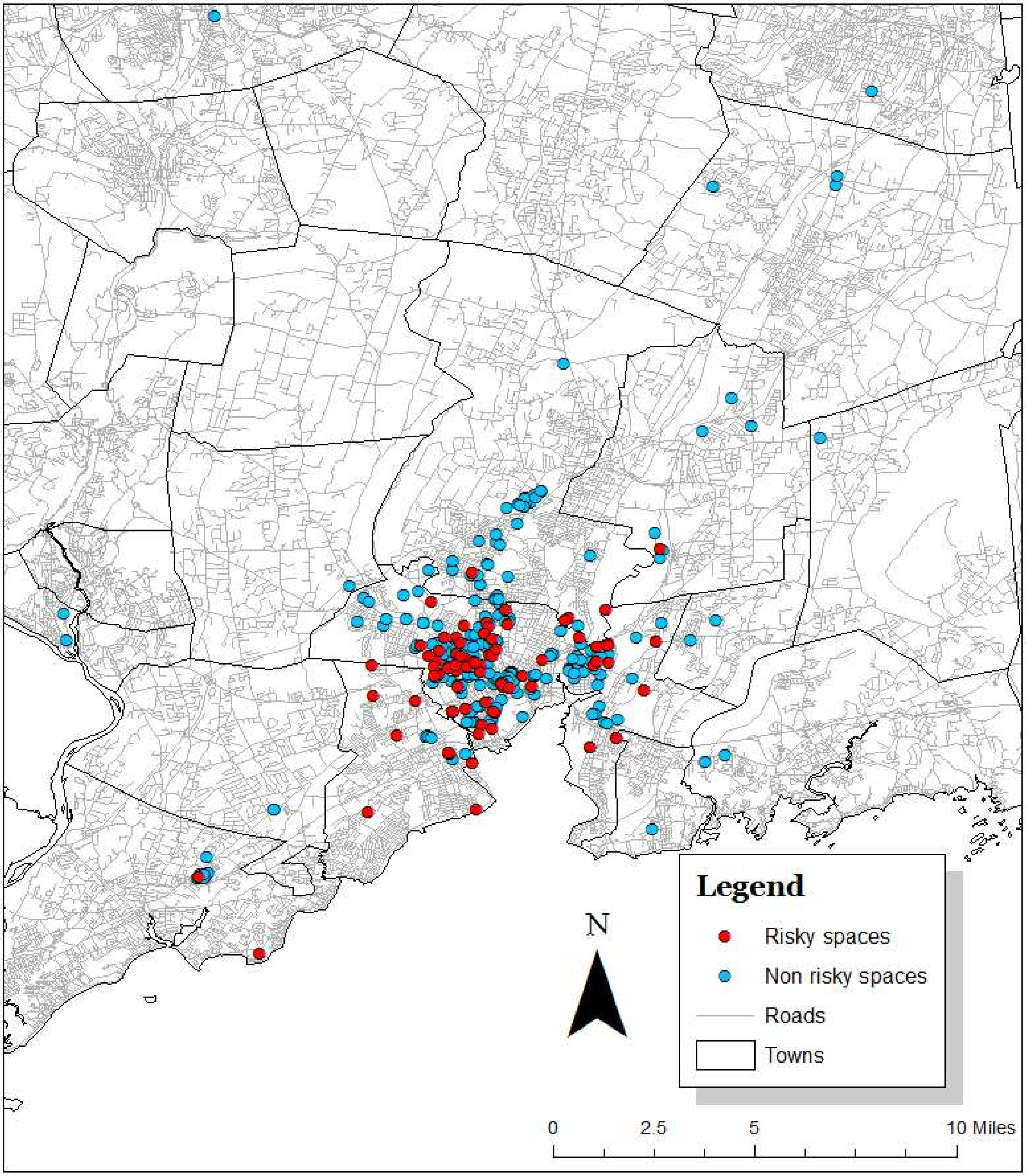

Table 3. Predictors of risky marijuana and alcohol use

	Model 1: Number of days smoked marijuana		Model 2: Use of marijuana more than one time per day		Model 3: Risky consumption of alcohol	
	B	95% CI	B	95% CI	B	95% CI
% Unemployed	0.0005	-0.0005, 0.0015	0.0050	-0.0020, 0.0120	0.0032	-0.0023, 0.0086
% Owner-occupied housing	0.0004	-0.0017, 0.0024	0.0118	-0.0014, 0.0251	-0.0034	-0.0160, 0.0092
Median household income	0.0002	-0.0018, 0.0022	-0.0056	-0.0199, 0.0087	0.0016	-0.0119, 0.0150
Crime index	-0.0004	-0.0017, 0.0010	0.0052	-0.0035, 0.0139	0.0013	-0.0089, 0.0115
Parks	-0.0005	-0.0021, 0.0012	-0.0030	-0.0140, 0.0080	-0.0017	-0.0150, 0.0115
Off-premise alcohol outlets	0.0000	-0.0013, 0.0014	0.0019	-0.0064, 0.0102	-0.0067	-0.0147, 0.0013
Police stations	-0.0001	-0.0015, 0.0012	0.0004	-0.0080, 0.0089	-0.0033	-0.0105, 0.0038
Churches	0.0002	-0.0023, 0.0026	0.0090	-0.0058, 0.0237	0.0004	-0.0128, 0.0137
Libraries	0.0003	-0.0011, 0.0017	-0.0003	-0.0095, 0.0089	0.0056	-0.0021, 0.0133
Network quality	**-0.0033***	-0.0052, -0.0015	**-0.0183***	-0.0292, -0.0074	**-0.0132***	-0.0223, -0.0040

**p<0.005*

Model 1 covariates: Age, education, number of alters

Model 2 covariates: Number of alters

Model 3 covariates: Age, income, number of alters

Table 4. Predictors of risky spaces

	Model 4: Risky spaces (marijuana and alcohol)		Model 5: Risky marijuana spaces		Model 6: Risky alcohol spaces	
	B	95% CI	B	95% CI	B	95% CI
% Unemployed	0.0008	-0.2693, 0.2710	-0.0983	-0.3557, 0.1591	0.2284	-0.2247, 0.6815
% Owner-occupied housing	0.0395	-0.5562, 0.6353	0.2499	-0.3624, 0.8622	-0.1540	-1.0730, 0.7651
Median household income	-0.3439	-0.8840, 0.1962	**-0.5692****	-1.1061, -0.0324	-0.0842	-0.8408, 0.6724
Crime index	-0.1220	-0.4093, 0.1654	-0.0827	-0.3926, 0.2271	-0.0229	-0.3748, 0.3291
Parks	-0.0143	-0.3364, 0.3078	0.0146	-0.2821, 0.3112	-0.4834	-1.2101, 0.2433
Off-premise alcohol outlets	0.1019	-0.3293, 0.5330	0.0849	-0.3211, 0.4909	**0.6701***	-0.1275, 1.4678
Police stations	-0.1236	-0.3801, 0.1330	-0.0741	-0.3234, 0.1752	-0.3117	-0.8646, 0.2413
Churches	-0.2067	-0.5521, 0.1387	-0.1468	-0.4889, 0.1953	-0.29414	-0.8717, 0.2889
Libraries	**-0.3509***	-0.7227, 0.0209	-0.2456	-0.6230, 0.1318	**-0.4316***	-0.9270, 0.0639
Network quality	**-1.1666*****	-1.5478, -0.7853	**-1.1153*****	-1.4836, -0.7471	**-0.7257*****	-1.2015, -0.2499

**p<0.10*

***p<0.05*

****p<0.005*

Model 4 covariates: Number of alters

Model 5 covariates: Number of alters

Model 6 covariates: Income, number of alters

Figure 2. Cluster of risky spaces using Getis-Ord Gi statistic